Job Searchers, Job Matches and the Elasticity of Matching

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JOB SEARCHERS, JOB MATCHES AND THE ELASTICITY OF MATCHING

by

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ABSTRACT

This paper stresses the importance of a specification of the matching function, where the measure of job matches as a dependent variable, corresponds to the stock of job searchers. In many empirical studies on the matching function this requirement has not been fulfilled. In this paper, we show that using unemployment outflow to a job as measure of job matches. related to unemployment and vacancies, gives a higher elasticity of matching with respect to unemployment, compared to the same elasticity when the flow of filled vacancies is used as measure of job matches. We have specified and estimated matching functions for The netherlands to illustrate our point.

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1. INTRODUCTION

The most practised model of aggregate labour market flows is the matching or hiring function. The matching function can be considered as a production function of matches or hires. It describes the technology of how the flow of job matches is related to the stock of job searchers and the stock of available jobs, much as a standard production function describes the technological relation between the flow of products and the stocks of production factors. There have been numerous efforts to specify and estimate matching functions for a number of countries. Cf. Pissarides (1986), Blanchard and Diamond (1989), Layard *et al.* (1991), Van Ours (1991,1995), Burda and Wyplosz (1994).

In the theoretical matching literature, job vacancies and unemployed workers are matched, yielding the flow of matches, i.e. the flow of unemployed persons finding employment. See, e.g. Pissarides (1990). In empirical studies of the matching functions, job matches are approximated by the flow of persons out of unemployment. However, while most of this outflow will involve the filling of a job, there may also be a number of unemployed who move out of the labour force. In order to counteract this flaw, in some studies only the flow of male unemployed is taken, under the assumption that the flow of unemployed moving out of the labour force mainly consists of women. Other studies use the total hires as an approximation for the number of matches. But hires not only include unemployed finding a job, also the flow of persons out of the labour force, like school-leavers, to a job and the flow of employed workers moving to another job, are included here. This means that no longer job vacancies and unemployed job searchers are matched, but instead vacancies and all job searchers. The same applies to the flow of filled vacancies, which sometimes is used to approximate the flow of matches. Vacancies are not necessarily filled by unemployed job searchers alone, they are open for any job searchers alike. So also in this case, the pool of unemployed job searchers in the matching function should be replaced by the pool of all job searchers. Despite all these different measures, in practically all studies job matches are related to the stock of unemployed and the stock of vacancies in the matching function. However, it is by now well-established that the workers moving from one job to another and not the unemployed constitute the larger part of the flow into employment. All these different measures for the flow of matches related to unemployment and vacancies, give different values for the elasticities in the matching function. These elasticities are relevant for economic policy measures. In The netherlands they may be used to tackle the problem of low labour participation. What is the effect of an increase in (unemployed) job searchers on the flow of job matches? Will increased unemployed job search enhance employment?

This paper shows that different measures of job matches and their corresponding stock of job searchers, does result in different matching elasticities. Estimation of matching functions for The Netherlands, where these different measures are used, supports our point. Using the outflow of unemployed to a job gives a higher matching elasticity with respect to unemployment than using the flow of filled vacancies.

The paper is organized as follows. The next section is about the importance of conformity of the stocks in the matching process and the flow of job matches. Section 3 proves that different measures of job matches give different matching elasticities. Estimates of the matching function, based on different measures of job matches and using pooled cross-section data on six sectors in The netherlands economy from 1988.2-1994.4, are presented Section 4 and finally Section 5 concludes.

2. JOB SEARCHERS AND JOB MATCHES

The process of matching workers and jobs is not an instantaneous process. Each worker and firm are engaged in a time-consuming (stochastic) process of waiting for and looking for an appropriate match. The matching process is formalized by the matching function, which gives the flow of new hires from some pool of job searchers as a function of that same pool of job searchers and the pool of available job vacancies.

$$F = cM(S, V), \tag{1}$$

where F is the flow of job searchers being matched to a job, M is the matching function, S is the stock of job searchers, V is the stock of available job vacancies, and c is a scale parameter. For the sake of reasoning, we assume time to be continuous.

This matching function is analogous to an aggregate production function. It shows that labour market flows generate delays in the finding of both jobs and workers, even when the matching process is very efficient. The efficiency of the matching process is represented by c in (1). Changes in the value of c Capture changes in the geographic and skill characteristics of workers and jobs or other differences between the two, as well as differences in search behaviour between job searchers.

Most of the empirical studies of the matching function are hampered by the fact that the flow of persons moving to a job do not always originate from the pool of job searchers in the matching function. In almost all studies, the pool of job searchers equals the stock of unemployed. In that case, ideally, the flow of matches should equal the flow of hires from unemployment. However, some studies approximate the flow of matches by the total hires. In this case the matches include much more than just the flow from unemployment into employment. Many vacancies are filled by workers moving from one job to another. In addition, a substantial part of the vacancies are filled by the flow of persons out of the labour force to a job, mostly school-leavers. So in this case, the stock of job searchers is much larger than the stock of unemployed. On the other hand, the job being filled does not necessarily have to be a vacancy. It can be an idle job or the unemployed can start her own business, etc. So also the stock of available jobs is probably larger than the stock of vacancies. This latter argument does not apply when the flow of filled vacancies are used as an approximation of the Aow of matches. Here, the pool of available jobs is indeed the stock of vacancies. However, a vacancy does not necessarily have to be filled by an unemployed job searcher. Employed job searchers and job searchers out of the labour force may equally well fill a vacancy. Hence, the pool of job searchers is, also in this case, much larger than just the stock of unemployed. Nevertheless, in all empirical studies, where matches are total hires or filled vacancies, unemployment is assumed to be sufftcient to represent the job searchers in the matching function. Cf. e.g. Blanchard and Diamond (1989), Van Ours (1991), Gorter and Van Ours (1994).

Many other studies use the outflow out of unemployment to approximate the flow of matches. This means that the actual flow of job matches by unemployed is overestimated, because no account is being taken of the unemployed moving out of the labour force. Sometimes, one tries to prevent this flaw by applying only the male outflow out of unemployment, assuming that mostly female unemployed move out of the labour force. Cf. Pissarides (1986), Layard *et* al. (1991), Burda and Wyplosz (1994). Also in this case, the persons moving out of unemployment do not necessarily fill a vacancy. Unreported vacancies (idle jobs) and the fact that many unemployed may start-up their own business, means that the pool of available jobs is underestimated.

The fact that in many studies the measure of job matches on the one hand does not correspond to the origin of the workers filling the job and the origin of the available jobs on the other hand. may bias the elasticity of the matching process with respect to the pool of job searchers and vacancies. Table 1 presents a comparison of studies of the matching function for a number of countries and shows the relation between certain measures of job matches and the values of the matching elasticity. It presents the dependent variable in (1) and shows the range of measures used to represent this flow of matches. It also reports the frequency of the data and the elasticities of matching with respect to the stock of job searchers, usually unemployed, and vacancies.

Table 1 shows a dichotomy for the values of the matching elasticity with respect to unemployment, α, and the measure of job matches. When the dependent variable is the outflow of unemployed (UO) or the hires from unemployed (HU), the value of $\alpha > 0.5$. On the other hand, if the dependent variable is the total hires (H), the flow of filled vacancies (F) or the hires from employment (HE), we find $\alpha < 0.5$. The value of α for the flow from persons not in the labour force (HO) is ambiguous.

* Table 1 somewhere here *

The flow of matches is in principle a continuous variable. The frequency of the data used to estimate the matching function should be of a high frequency in order to take account of this flow character. Therefore, in many studies monthly and quarterly data were used. However, for The Netherlands, only adequate annual data were available, so far. In particular, the annual flows of vacancies are large in proportion to the stock. The average vacancy duration is about two months. The duration of unemployment is about one year. In this light, it seems more appropriate to estimate the matching function with quarterly data than with annual data.

The quarterly data set we use has the advantage that the measures of job matches that are available, the flow of unemployed to a job and the flow of filled vacancies, can be linked to the correct stocks of job searchers and available jobs. We only need to assume that the unemployed find a job only by filling a vacancy. Hence, there is no job finding via idle jobs (unreported vacancies) or starting ones own business. Second, we assume that the total stock of job searchers, who are eligible to fill any vacancy, consists of unemployed job searchers and of job searchers with a job and job searchers not in the labour force. We distinguish unemployed job searchers who receive an unemployment insurance benefit and unemployed who are on unemployment support.

Another advantage of our data set is that it covers a period, 1988-1994, in which no major changes in the definition of the variables involved occurred. The final major change in definitions in unemployment, vacancies and unemployment outflow was in 1987. In that year the official vacancy statistics were collected based on a survey, which is argued also to take account of unreported vacancies, and there was a change in legislation with respect to the unemployment insurance act. For more details on our data set we refer to Appendix 1.

3. THE ELASTICITY OF MATCHING

In this section we will show that different measures of matching, and hence different stocks of job searchers, imply quite different values for the elasticities of matching. Assume that in the labour market we have unemployed job searchers, decomposed into persons on unemployment insurance and on unemployment support, employed job searchers and job searchers not in the labour force. Figure 1 presents the flows between the different labour market states that are relevant in our study.

* Figure 1 somewhere here *

In Figure 1, the unemployed with an unemployment insurance benefit, U, and the unemployed on unemployment support, U_s, together build registered unemployment, UR. The job searchers not in the labour force, or non-participants, are labelled N. Only a certain proportion of this group searches for a job, mainly school-leavers and married women re-entering the labour market after raising their children. Finally, E are the employed persons. Also in this group, there is a certain proportion looking for another job, leading to job-to-job flows. This means that $S=UR+\phi_1 E+\phi_2 N$, where $0<\phi_i<1$ and $i=\{1,2\}$. Furthermore, we assume that all inflow into E occurs by means of filling a vacancy. The total inflow into employment, or the total flow of filled vacancies, F, consists of the flow of unemployed on unemployment insurance to a job, F_{ue}, the flow of unemployed on unemployment support and non-participants to a job, F_{ne}, and the flow of employed finding a another job, F_{ee}. This means $F=F_{ue}+F_{ne}+F_{ee}$. Based on earlier arguments, a matching function based on F_{ue} should contain U as stock of job searchers, whereas a matching function based on F should have S as stock of job searchers.

The matching function (1) is usually specified in a Cobb-Douglas form with constant returns to scale. So in terms of (1), we find

$$F = cS^{\alpha}V^{1-\alpha}, \tag{2}$$

where α is the matching elasticity with respect to the stock of job searchers. It shows the effect of job matches to a change in S or V.

In terms of Figure 1, we can rewrite (2) as

$$F = c(U+X)^{\alpha}V^{1-\alpha}, \tag{3}$$

where X is the stock of all job searchers except those with an unemployment insurance benefit. X consists of job searchers on unemployment support, employed job searchers and job searchers not in the labour force. We assume that this stock X has a pro-cyclical character. An economic upswing implies favourable opportunities of finding a job, so X will increase. In a downturn the opposite holds. Suppose X can also be written in a Cobb-Douglas form,

$$X = \rho U^{\beta}E^{\gamma}, \tag{4}$$

where $\beta<0$, $\gamma>0$ and ρ is some scale parameter.

Under these assumptions, the flow of unemployed to a job, F_{ue}, can be written as

$$F_{ue} = \frac{U}{U+X}F = \xi\, U(U+X)^{\alpha-1}V^{1-\alpha} \qquad \text{i.e.}$$

$$\frac{F_{ue}}{U} = \xi\left(\frac{V}{U+X}\right)^{1-\alpha}, \tag{5}$$

where $\xi = c\rho$.

This implies that we can also rewrite (3) as

$$\frac{F}{V} = c\left(\frac{U+X}{V}\right)^{\alpha}. \tag{6}$$

In general terms, the matching function, based on (2) without assuming constant-returns-to-scale, can be specified as

$$F = c(U+X)^{\alpha}V^{\delta} \qquad \text{i.e.,}$$

$$F = c(U+\rho U^{\beta}E^{\gamma})^{\alpha}V^{\delta}. \tag{7}$$

This enables us to write

$$\frac{\partial F}{\partial U} = \alpha\frac{F}{U+\rho U^{\beta}E^{\gamma}}(1+\beta\rho U^{\beta-1}E^{\gamma}). \tag{8}$$

So for the elasticity of matching with respect to unemployment, $(\partial F/\partial U)(U/F)$, this implies

$$\frac{\partial F}{\partial U}\frac{U}{F} = \alpha^{*} = \alpha\frac{1+\beta\rho U^{\beta-1}E^{\gamma}}{1+\rho U^{\beta-1}E^{\gamma}}. \tag{9}$$

From (9) it is easy to derive that $\alpha^{*} < \alpha$ if $\beta < 1$.

On the other hand, from (5) we can derive that

$$F_{ue} = \xi U(U+\rho U^{\beta}E^{\gamma})^{\alpha-1}V^{\delta}. \tag{10}$$

So in this case we find,

$$\frac{\partial F_{ue}}{\partial U} = \frac{F_{ue}}{U}\left(1+(\alpha-1)\left[\frac{1+\beta\rho U^{\beta-1}E^{\gamma}}{1+\rho U^{\beta-1}E^{\gamma}}\right]\right). \tag{11}$$

The elasticity of matching with respect to unemployment, $(\partial F_{ue}/\partial U)(U/F_{ue})$, is

$$\frac{\partial F_{ue}}{\partial U}\frac{U}{F_{ue}} = \alpha \left(\frac{1+\rho U^{\beta-1}E^{\gamma}\left(\frac{1+\alpha\beta-\beta}{\alpha}\right)}{1+\rho U^{\beta-1}E^{\gamma}} \right). \tag{12}$$

Elasticity (12) shows that $\alpha^{**} > \alpha$ when $(1 + \alpha\beta-\beta)/\alpha > 1$. In other words, under the assumption that (1-a) > 0, this implies that $\alpha^{**} > \alpha$ when $\beta < 1$.

Hence, when matches are represented by the flow of filled vacancies F and $\beta < 1$, we find an elasticity of matching with respect to unemployment of $\alpha^{*} < \alpha$. When matches are represented by the flow of hires from unemployment to employment F_{ue} and $\beta < 1$, we find an elasticity of matching with respect to unemployment of $\alpha^{**} > \alpha$. This means that $\alpha^{**} > \alpha^{*}$ when $\beta < 1$. Or, when matches are respresented by the flow of hires from unemployment, the matching elasticity with respect to unemployment is larger then the matching elasticity with respect to unemployment in case matches are respresented by the flow of filled vacancies. This proves our point made in Table 1 about the dichotomy in the matching elasticities with different measures for job matches. The only condition we have to test is whether $\beta < 1$.

4. EMPIRICAL RESULTS

The necessary condition under which the matching elasticity with respect to unemployment, in case matches are hires from unemployment, is larger that the matching elasticity, in case matches are the filled vacancies, is that $\beta < 1$. This means that the elasticity of all job searchers, except those on unemployment insurance, with respect to the number of persons with an unemployment insurance benefit is smaller than unity.

This condition is likely to hold, because $X=S-U$. So if $\partial X/\partial U=\partial(S-U)/\partial U=\partial S/\partial U-1 < 0$ and hence $\partial S/\partial U < 1$, then most certainly $\beta=(\partial X/\partial U)(U/X) < 1$. Testing this premise means testing whether the correlation between X and U is negative. Another way is to estimate equation (4) directly and test whether $\beta < 1$.

The simple correlation coefficient between X and U is $\rho_{X,U}=-0.67$, with a t-statistic of 4.2, which implies that $\beta < 1$, and in fact $\beta < 0$. The actual value of the elasticity β is determined in Table 2, where equation (4) is estimated for The Netherlands. We find that $\beta=-0.12$, with a t-statistic of 1.74, hence β is negative at a 10 percent significance level. This provides ample evidence for the difference in matching elasticity for different measures of matching, that was proved in the previous section.

* Table 2 somewhere here *

As a final part of this section, we present the estimation results of the matching function based on pooled cross-section time series, from 1988.2-1994. It concerns flow data based on a number of sectors in the Dutch economy. See also Appendix 1 and 2. The outflow rate of persons with an unemployment insurance benefit to a job is linked to the pool of unemployment insurance benefit recipients and the pool of vacancies. We assume a matching function specified in Cobb-Douglas form with constant returns-to-scale, as in equation (2).

$$\log[F_{ue,i,t}/U_{i,t-1}] = \gamma_i + \alpha_i \log(V_{i,t-1}/U_{i,t-1}) + \epsilon_{1,i,t}, \tag{13}$$

where $\epsilon_{1,i}$ is an error term and index i refers to the sector involved ($i = 1,..,6$).

If we take the flow of job matches to be equal to the flow of filled vacancies, then the associated pool of job searchers consists of employed job searchers, unemployed job searchers and job searchers out of the labour force. Adequate data on all of these three stocks are not available. Obviously, we do have the pool of unemployed job searchers. Based on Boeri (1995), we assume that a fixed proportion of 10 percent of the employed are searching for another job and, based on scattered evidence of Statistics Netherlands, we assume that 7 percent of non-participants actively search for a job. Finally, we assume that workers in one sector search only for another job in the same sector. The stock of available jobs is of course represented by the stock of vacancies. Assuming, like before, a Cobb-Douglas form with constant-returns-to-scale,

$$\log[F_{i,t}/S_{i,t-1}] = \mu_i + \beta_i \log(V_{i,t-1}/S_{i,t-1}) + \epsilon_{2,i,t}, \tag{14}$$

where S_i is the stock of job searchers, β_i is the matching elasticity per sector and $\epsilon_{2,i}$ is an error term.

The labour market efficiency for each sector in (13) is given by γ_i and in (14) by μ_i. This equals $\log c_i + \log \rho_i$ and $\log c_i$, respectively, in terms of (5) and (3). In practice, this means that efficiency is represented by six sector dummies, in both specifications. That makes equations (13) and (14) a so-called fixed-effect model. In order to be able to give more information, we will also include two additional variables representing heterogeneity between job searchers on the labour market. The first is a mismatch indicator, which equals the absolute value of the residuals of a UV-curve regression, where $\log U$ is regressed on sector dummies and $\log V$. This mismatch indicator refers to shifts in the UV-curve. For the 'SV-curve' a similar measure is constructed, where instead of U the total number of job searchers S is taken. The second variable we use is a measure for the number of long-term unemployed in each sector. The more long-term unemployed, the less is the outflow rate of unemployed. Since we have no information on the stock of long-term unemployed in each sector, we have used as an approximation the log of the ratio of persons leaving the unemployment insurance system because their maximum benefit duration has expired and the total outflow out of the unemployment insurance system. When this ratio increases, this means that unemployed have a hard time finding a job and the outflow rate will fall.

Specification (13) and (14) contain group dummies for each of the six sectors. We first test whether this fixed-effect specification of (13) and (14) is correct or whether a random-effect specification is more appropriate. A random effect model has no group dummies, so in (13) and (14), $\gamma_i=\gamma$, $\mu_i=\mu$ and the error $\epsilon_{k,i,t}=\eta_{k,i}+\upsilon_{k,i,t}$, where $k=\{1,2\}$, η is a random term and υ is an error term. We conduct a Hausman test on the null hypothesis that the random-effect model is the correct specification. For model (13), we find $\chi^2(8)=23.90$, which implies that the fixed-effect model (13) cannot be rejected in favour of the random-effect model. For model (14), this test cannot be performed, because the estimated variance of η_2 is close to zero. When we take $\beta_i=\beta$, it can be performed and yields $\chi^2(2)=5{,}66$, which is significant at 6 percent. We will specify both models in fixed-effect format.

The estimation results for matching model (13) are presented in Table 3. This Table shows that the matching elasticities, with respect to vacancies, differ per sector. It is lowest for construction with 0.13 and highest for non-commercial services with 0.31. Especially, the latter sector seems to have a higher matching elasticity than the other sectors, who are all around 0.2. Note that the insignificant positive value of our mismatch indicator is counter-intuitive. An increase in long-term unemployment, however, means a fall in labour market efficiency and thus in the matching rate, as expected.

* Table 3 somewhere here *

Table 4 presents the estimation results of (14). Note that the matching elasticities with respect to vacancies, when the flow of filled vacancies is used as dependent variable, are much higher then those found for the flow of unemployed to a job. In Table 4 the elasticities vary from 0.45 for construction, to 0.66 for commercial services 2. In this model, there is no significant effect of long-term unemployed, but there is a positive effect of the mismatch indicator, based on shifts in the SV-curve.

* Table 4 somewhere here *

Next, we conduct a test on the hypothesis of an equal matching elasticity for all sectors, *i.e.* $\alpha_i=\alpha$ and a zero effect of mismatch in the model of Table 3. This may also affect the efficiency as represented by γ_i. Conducting an F-test on this parameter restriction yields $F(6,148)=2.14$, which is about equal to the 5 percent significance level. Table 3 also gives this simplification. The overall matching elasticity for model (13) equals about 0.2.

A similar specification analysis can be applied to the model of Table 4. A test on the equality of the matching elasticities for all sectors, $\beta_i=\beta$, and a zero effect of long-term unemployment and mismatch, yields for this model $F(6,130)=2.38$, which is not significant at 5 percent, but it is at 2.5 percent. In other words, there is a significant difference in the elasticities at the 5 percent level. The overall matching elasticity for model (6) is about 0.5.

Comparison with Table 1 indicates that the elasticity for model (13) is in line with the values found by those studies who have used the unemployment outflow or the hires from unemployment as a measure of job matches. In that case the stock of unemployed is the relevant pool of job searchers. The elasticity found for model (14) is also in line with the values found by those studies who have used total hires or filled vacancies as a measure of job matches. However, in most studies, this measure of matches is related to the stock of unemployed, while in fact it should be related to unemployed, employed job searchers and job searchers not in the labour force. It appears that the stock of unemployed serves as a reasonable approximation for the stock of all job searchers.

Finally, we report. in Table 5, the sectoral differences in labour market efficiency for the two models. If we normalize the efficiency of agriculture to 1, we find that all other sectors have lower levels of efficiency for model (13). In the service sector the efficiency is about half the value in agriculture. For someone with an unemployment insurance benefit it is easier to find a job in agriculture than in the service sector. Note that the ranking of the efficiency of commercial services 2 and non-commercial services has reversed when moving to the simplified model. This indicates that it matters for the efficiency, whether we apply parameter restrictions to the model of Table 3 column 2.

For model (14), we find that the efficiency of matching in the non-commercial service sector is highest, whereas in construction is lowest. The results imply that, for all job searchers, it easier to find a job in the service sector than in the other sectors. Combining this result with what was found in the previous paragraph, implies that employed job searchers and job searchers not in the labour force find a job in the service sector relatively easily, whereas this sector is relatively closed for unemployed job searchers. Note that the ranking in efficiency between sector changes dramatically here, when the models of Table 4 column 2 and column 3 are compared. This is because the hypothesis of equal matching elasticities between sectors for this model could not accepted at 5 percent.

* Table 5 somewhere here *

5. CONCLUDING REMARKS

This paper studies the properties of the matching function, where the measure of job matches and the pool of job searchers are consistent with each other. When we assume job matches to be equal to hires from unemployment, we find a matching elasticity with respect to unemployment of 0.8 and with respect to vacancies of 0.2. When we approximate matches by the flow of filled vacancies, we find a matching elasticity with respect to the entire stock of job searchers (and with vacancies) of 0.5. These results are in line with those of Van Ours (1995), where a distinction is made between unemployed and employed job searchers. There, the matching elasticity with respect to unemployment is about 0.6 when matches equal the hires from unemployment. When the matches of employed job searchers are considered, the matching elasticity with respect to the stock of employed job searchers equals some 0.3. The stock of employed job searchers is a fixed proportion of total employment, like we assume in this paper.

Our study stresses the importance of other job searchers in the matching process than unemployed. Burgess (1993,1994) already pointed out that employed job searchers build the largest flow into employment and affect the standard matching approach substantially. We argue that in a standard matching fùnction, the stock of job searchers should correspond to the origin of the flow of job matches. In many studies, only the stock of unemployed job searchers is used. This paper shows that when job matches are associated with the flow of unemployed to a job, the matching elasticity with respect to unemployment is larger than the matching elasticity with respect to unemployment, in case matches are represented by the flow of filled vacancies.

Our values of the matching elasticity imply that, when the hiring rate from unemployment represents the matching rate, an increase in layoffs, has a much larger effect on the matching rate than an increase in vacancies. Stimulating labour demand, by increasing the number of vacancies, only has a minor effect on the hiring rate from unemployment. On the other hand, it does have a large effect when the flow of filled vacancies represents job matches. In other words. stimulating labour demand leads to increased job search by other job searchers than unemployed. Many of the vacancies, created as a cause of stimulating labour demand, are filled by employed job searchers and new entrants on the labour market. This corresponds to results of other studies, like the Ministry of Social Affairs (1993).

REFERENCES

Albæk, K. and H. Hansen, 1995, 'Estimating Aggregate Labor Market Relations, mimeo, University of Copenhagen.

Anderson, J.M. and S.M. Burgess, 1994, 'Empirical Matching Functions: Estimation and Interpretation Using Disaggregate Data', mimeo, Dartmouth College and NBER.

Antolin, P., 1994, 'Unemployment Flows and Vacancies in Spain', mimeo, Nuffield College Oxford.

Blanchard, P. and 0. Blanchard, 1989, 'The Beveridge Curve', *Brookings Papers on Economic Activity,* 1, 1-76.

Boeri, T., 1995, 'On the Job Search and Unemployment Duration', Working Paper No. 38, European University Institute, Badia Fiesolana, Italy.

Burda, M. and C. Wyplosz, 1994, 'Gross Worker and Job Flows in Europe' *European Economic Review, 38,* 1287-1315.

Broersma, L., 1994, 'Competition Between Employed and Unemployed Workers', mimeo, Free University Amsterdam.

Burgess, S.M., 1993, 'A Model of Competition Between Unemployed and Employed Job Searchers: An Application to the Unemployment Outflow Rate in *the* UK', *Economic Journal,* 108, 1190-1204.

Burgess, S.M., 1994, 'Matching Models and Labour Market Flows', *European Economic Review, 38,* 809-816.

Eriksson, T. and J. Pehkonen, 1995, 'The Unemployment Outflow in Finland 1969-1994', mimeo, Aarhus School of Business. Denmark.

Gorter, C. and J. Van Ours, 1994, 'Matching Unemployment and Vacancies in Regional Labour Markets: An Empirical Analysis for The Netherlands', *Papers in Regional Science, 73,* 153-167.

Layard, R., S. Nickell and R. Jackman, 1991, *Unemploymenr,* Oxford University Press.

Ministry of Social Affairs. *Sociale Nota*, The Hague (in Dutch).

Mumford, K. and P. Smith, 1995, 'Labour Market Flows, Cycles and Hiring in Australia', mimeo, University of York.

Pissarides, C.A.. 1986, 'Unemployment and Vacancies in Britain', *Economic Policy*, *3,* 499-559.

Pissarides, C.A., 1990, *Equilibrium Unemployment Theory*, Basil Blackwell.

Schettkat, R., 1993, 'Matching Functions: The Flow Approach', mimeo, Wissenschafts-zentrum Berlin.

Van Ours, J.C., 1991, 'The Efficiency of the Dutch Labour Market in Matching Unemployment and Vacancies', *De Economist*, 139, 358-378.

Van Ours, J.C., 1994, 'Matching Unemployment and Vacancies at the Public Employment Office', *Empirical Economics,* 19, 37-54.

Van Ours, J.C., 1995, 'An Empirical Note On Employed and Unemployed Job Search' *Economics Letters*, *49, 447-452.*

Table 1. An international comparison of matching elasticities.

	country	Dependent variable	data	Elasticity v	u
Pissarides (1986)	UK	UO	quarterly	0.3	0.7
Blanchard and Diamond (1989)	USA	H	monthly	0.6	0.4[1]
		HU	monthly	0.2	0.6[1]
		HO	monthly	0.2	0.6[1]
Layard et al. (1991)	UK	UO	quarterly	0.3	0.7
Van Ours (1991)	Netherlands	F	annual	0.6	0.4
Burgess (1993)	UK	UO	quarterly	0.4	0.6
Schettkat (1993)	Germany	H	annual	0.2	0.0
		HU	annual	0.2	0.7
Burda and Wyplosz (1994)	France	UO	monthly	0.3	0.7
	Germany	UO	monthly	0.3	0.7
	Spain	UO	monthly	0.2	0.8
	UK	UO	monthly	0.3	0.7
Van Ours (1994)	Netherlands	F	annual	0.6	0.4
Gorter and Van Ours (1994)	Netherlands	F	annual	0.7	0.3
Anderson and Burgess (1994)	USA	H	annual/panel	0.8	0.4
		HN	annual/panel	0.7	0.3
		HE	annual/panel	1.0	0.7
Broersma (1994)	Netherlands	UO	annual	0.3	0.7
Antolin (1994)	Spain	UO	annual	0.2	0.8
Van Ours (1995)	Netherlands	HU	annual	0.3	0.7
		HE	annual	0.7	0.3
Albæk and Hansen (1995)	Denmark	HN	quarterly	0.3	0.7
Mumford and Smith (1995)	Australia	H	monthly	0.3	0.3
		HU	monthly	0.1	0.6
		HO	monthly	0.4	-0.3[2]
Eriksson and Pehkonen (1995)	Finland	UO	quarterly	0.2	0.8

Explanation: UO is unemployment outflow (in some cases only males), H is total hires, HU is hires from unemployment, HO hires from out of the labour force, F is filled vacancies, HN is hires from non-employment, HE is hires from employment.

[1] The 'unemployment' pool is a combination of unemployed job searchers and job searchers out of the labour force.

[2] Here, is 'unemployment' pool is the number person not in the labour force.

Table 2. Estimation results of equation (4).

The variables in equation (4) contain unit roots and cointegration between the three variables cannot be rejected, as $DW=0.82$. The simplified model in error-correction form is presented below .

$$\Delta\log(X_t) = \underset{(1.754)}{1.235} \; - \underset{(-1.727)}{0.172} \left[\log(X_{t-1}) + \underset{(1.743)}{0.118} \log(U_{t-1}) \right]$$

$R^2 = 0.865$ $\sigma = 0.0151$ DW = 1.719 T = 24 (1989.1-1994.4)

The long-term equilibrium relation between X and U is given by the error-correction part,

$$\log X = -0.12 \log U,$$

where the coefficient of $\log U$ equals the elasticity β.

Table 3. Estimation results of matching function (13)

Dependent variable:		$\log(F_{ue,i,t}/U_{i,t-1})$	
constant	-0.910 (-6.487)	-0.898 (-6.369)	-0.885 (-6.308)
group dummies D_{man}	-0.373 (-4.480)	-0.384 (-4.597)	-0.406 (-5.514)
D_{con}	-0.180 (-4.649)	-0.179 (-4.593)	-0.179 (-6.096)
D_{cs1}	-0.777 (-8.634)	-0.784 (-8.678)	-0.805 (-9.832)
D_{cs2}	-0.599 (-8.775)	-0.605 (-8.818)	-0.659 (-10.38)
D_{ncs}	-0.512 (-5.207)	-0.529 (-5.377)	-0.663 (-7.996)
log of VU ratio$_{t-1}$ *for.*			
aggregate economy			0.176 (15.08)
agriculture	0.156 (7.634)	0.149 (7.402)	
manufacturing	0.186 (6.975)	0.178 (6.744)	
construction	0.132 (3.381)	0.129 (3.287)	
commercial services 1	0.189 (5.798)	0.179 (7.744)	
commercial services 2	0.220 (8.3 17)	0.202 (8.288)	
non-commercial services	0.306 (6.108)	0.292 (5.827)	
mismatch,	0.128 (1.686)		
long-term unemployment,	-0.170 (-4.131)	-0.170 (-4.109)	-0.174 (-4.250)
R^2	0.956	0.955	0.952
σ	0.104	0.105	0.106
N×T	162	162	162

Table 4. Estimation results of matching function (14)

Dependent variable:		$\log(F_{i,t}/S_{i,t-1})$	
constant	-1.670 (-6.557)	-1.593 (-10.14)	-1.409 (-14.96)
group dummies D_{man}	0.674 (2.961)	0.663 (3.043)	0.155 (3.281)
D_{con}	-0.014 (-0.059)	-0.018 (-0.058)	0.106 (2.503)
D_{cs1}	0.856 (3.295)	0.806 (3.461)	0.736 (13.82)
D_{cs2}	0.598 (2.217)	0.547 (2.037)	-0.053 (-1.384)
D_{ncs}	1.184 (3.463)	1.106 (3.357)	0.497 (10.95)
log of VU ratio$_{t-1}$ for:			
aggregate economy			0.540 (30.90)
agriculture	0.511 (16.26)	0.504 (16.81)	
manufacturing	0.631 (15.26)	0.630 (15.17)	
construction	0.476 (13.42)	0.465 (13.66)	
commercial services 1	0.513 (9.070)	0.502 (9.032)	
commercial services 2	0.636 (14.33)	0.624 (14.28)	
non-commercial services	0.668 (8.722)	0.652 (8.538)	
mismatch,	0.474 (1.725)		
long-term unemployment,	-0.022 (-0.295)		
R^2	0.974	0.974	0.970
σ	0.127	0.128	0.133
$N \times T$	162	162	162

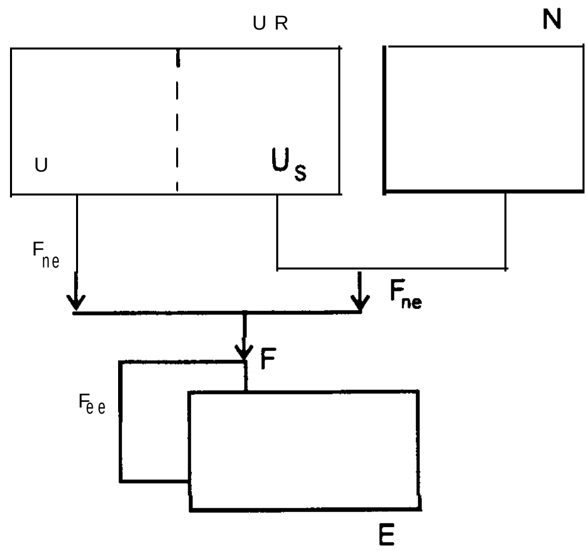
Table 5. **Sectoral labour market efficiency and 95 percent confídence interval**

Sector[a]	Model: Table 3 column 2	Table 3 column 3
Manufacturing	0.68 (0.58 - 0.80)	0.67 (0.58 - 0.71)
Construction	0.84 (0.77 - 0.90)	0.84 (0.79 - 0.89)
Commercial services 1	0.46 (0.38 - 0.54)	0.45 (0.38 - 0.53)
Commercial services 2	0.55 (0.48 - 0.63)	0.52 (0.46 - 0.59)
Non-commercial services	0.59 (0.49 - 0.71)	0.51 (0.44 - 0.61)

Sector[a]	Model: Table 4 column 2	Table 4 column 3
Manufacturing	1.94 (1.27 - 2.97)	1.17 (1.06 - 1.28)
Construction	0.98 (0.64 - 1.49)	1.11 (1.02 - 1.21)
Commercial services 1	2.24 (1.42 - 3.53)	2.10 (1.88 - 2.32)
Commercial services 2	1.73 (1.02 - 2.92)	0.95 (0.88 - 1.02)
Non-commercial services	3.02 (1.58 - 5.75)	1.65 (1.51 - 1.80)

[a] Effkiency of agriculture is normalized to 1.

Figure 1. Flows into employment.



APPENDIX 1. DATA: SOURCES AND DEFINITIONS

$F_{ue,i}$ — Flow of persons with unemployment insurance benefit to a job, for sector *i*.
source: Sociale verzekeringsraad, ***Het beroep op de Werkloosheidswet, omvang en ontwikkeling.***

F — Flow of filled vacancies for sector *i*
source: Centra1 Bureau of Statistics, ***Sociaal-economische maandstatistiek.***

U_i — Number of persons receiving unemployment insurance benefit, for sector *i*.
source: Sociale verzekeringsraad, ***Het beroep op de Werkloosheidswet, omvang en ontwikkeling.***

S_i — Total number of job searchers, consisting of unemployed and employed job searchers and job searchers not in the labour force: $UR+\phi_1 E_i+\phi_2 N$, where we implicitly assume that unemployed and non-participant job searchers may apply to any sector and employed job search mainly takes place within the same sector. Further, ϕ_1 and ϕ_2 represent the fraction employed and non-participants searching for a job, with $\phi_1=0.10$ and $\phi_2=0.07$.

UR — Registered unemployment, composed of both persons with an unemployment insurance benefit and persons on unemployment support.
source: Centra1 Bureau of Statistics, ***Sociaal-economische maandstatistiek.***

E_i — Number of jobs in sector *i*.
source: Centra1 Bureau of Statistics, ***Sociaal-economische maandstatistiek.***

N — Number of persons not in the labour force (non-participants), defined as *POP1464-E-UR*, where ***POP1464*** is the population of working age, ***i.e.*** between 14 and 64 years old and ***E*** is overall employment, or $E=\Sigma E_i$. ***POP1464*** is interpolated to give quarterly data.
source: Central Bureau of Statistics, ***Statistical Yearbook.***

V_i — Number of vacancies for sector i.
source: Centra1 Bureau of Statistics, ***Sociaal-economische maandstatistiek.***

mismatch — mismatch indicator, based on shifts in UV- or SV-curve, defined as follows,
mismatch = $\epsilon_{i,t}$ |, where $\epsilon_{i,t}$ comes from the regression
$\log(U_{i,t}) = \gamma_i + \alpha\log V_{i,t} + \epsilon_{i,t}$ or $\log(S_{i,t}) = \gamma_i + \alpha\log V_{i,t} + \epsilon_{i,t}$.

LTU — measure of long-term unemployment, defined as the log of the outflow from

unemployment insurance due to expiry of maximum benefit duration (UO_{max}) and total outflow (UO_{tot}), or LTU = $\log(UO_{max}/UO_{tot})$.
source: Sociale verzekeringsraad, ***Het beroep op de Werkloosheidswet, omvang en ontwikkeling.***

APPENDIX 2. SECTORAL CLASSIFICATION

This Appendix describes the classification of the sectors we distinguish in terms of the SBI-index in The Netherlands (similar to the SIC-classification). SBI 1, mining, and SBI 5, public utility, have been omitted. The first is very smal1 in The Netherlands and the latter is also smal1 and more or less constant over the period 1989-1994.

Sector	SBI	Description
Agriculture	0	agriculture, fishery
Manufacturing	2/3	manufacturing
Construction	5	construction and installation
Commercial services 1	6 and 8	hotels, restaurants, wholesale and retail trade, banks, real estate and insurance companies
Commercial services 2	7	transport, storage and communication
Non-commercial services	9	other (non-commercial) services, government